

# Impacts of climate change on streamflow in the Upper Mississippi River Basin: A regional climate model perspective

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Received 14 April 2003; revised 22 January 2004; accepted 11 February 2004; published 15 May 2004.

[1] Impact of climate change on streamflow in the Upper Mississippi River Basin is evaluated by use of a regional climate model (RCM) coupled with a hydrologic model, Soil and Water Assessment Tool (SWAT). The RCM we used resolves, at least partially, some fine-scale dynamical processes that are important contributors to precipitation in this region and that are not well simulated by global models. The SWAT model was calibrated and validated against measured streamflow data using observed weather data and inputs from the U.S. Environmental Protection Agency Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) geographic information systems/database system. Combined performance of SWAT and RCM was examined using observed weather data as lateral boundary conditions in the RCM. The SWAT and RCM performed well, especially on an annual basis. Potential impacts of climate change on water yield and other hydrologic budget components were then quantified by driving SWAT with current and future scenario climates. Twenty-one percent increase in future precipitation simulated by the RCM produced 18% increase in snowfall, 51% increase in surface runoff, and 43% increase in groundwater recharge, resulting in 50% net increase in total water yield in the Upper Mississippi River Basin on an annual basis. Uncertainty analysis showed that the simulated change in streamflow substantially exceeded model biases of the combined modeling system (with largest bias of 18%). While this does not necessarily give us high confidence in the actual climate change that will occur, it does demonstrate that the climate change “signal” stands out from the climate modeling (global plus regional) and impact assessment modeling (SWAT) “noise.” *INDEX TERMS:* 1655 Global Change: Water cycles (1836); 1860 Hydrology: Runoff and streamflow; 1866 Hydrology: Soil moisture; *KEYWORDS:* climate change, streamflow, SWAT

**Citation:** Jha, M., Z. Pan, E. S. Takle, and R. Gu (2004), Impacts of climate change on streamflow in the Upper Mississippi River Basin: A regional climate model perspective, *J. Geophys. Res.*, 109, D09105, doi:10.1029/2003JD003686.

## 1. Introduction

[2] Streamflow characteristics, both mean and interannual variability, of the Upper Mississippi River Basin (UMRB) have far-reaching implications for the central United States. Following closely on the heels of the massive drought of 1988 in this region, which stranded barges below St. Louis, Missouri [Glantz, 1988], the Great Flood of 1993 created an \$18 billion impact [Changnon, 1996]. Analysis of this event exposed a profound range of implications, including environmental effects, economic effects, impacts on government entities, social impacts, and impact on a wider range of public policies [Changnon,

1996]. On the basis of a substantial amount of scientific analysis and retrospective diagnosis of decision-maker actions before, during and after this event, the summary of Changnon [1996] concluded with seven “lessons learned” and some “unresolved key issues,” among them being [Changnon, 1996, p. 318] “...a great need to develop more sophisticated river basin models that allow drastically improved flood forecasts.”

[3] We have examined this need for more sophisticated modeling procedures in the context of climate change to expose the strengths and weaknesses of linking global and regional climate models to a streamflow model to calculate streamflows consistent with a future climate scenario.

[4] Future scenario climates for mid to end of the twenty-first century as simulated by global climate models show generally a warming over the United States. Large uncertainties accompany global model projections of future changes in global mean precipitation, but increase on an annual basis seems to be most likely. Estimates of inter-model consistency in downscaled precipitation from global climate models [Intergovernmental Panel on Climate

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*Change (IPCC)*, 2001a] for the central United States show a small increase in December–January–February but lack of consistency on the sign of change or possibly a small decrease for June–July–August.

[5] Regional climates consistent with global changes are created by downscaling global climate model (GCM) results either by statistical or by dynamical (regional climate model (RCM)) methods. Numerous studies based on statistical methods for exploring impact of climate change at the watershed scale are summarized in the latest IPCC impacts report [IPCC, 2001b]. *Giorgi et al.* [1994a] showed that a nested regional model produced a more realistic simulation of precipitation over the United States than the driving global model alone and also that the estimated changes in climate were different: precipitation changes differed locally in magnitude, sign, and spatial and seasonal details.

[6] Several studies have investigated the impacts of climate change on the hydrology of a watershed. *Stone et al.* [2001] used RegCM [*Giorgi et al.*, 1993] to assess the impacts of climate change on water resources in the Missouri River Basin. They found dramatic increase in water yield (100% or more) for the northern region of the basin while the southern region showed a decrease of up to 80%.

[7] In a follow-up study, *Stone et al.* [2003] examined the impact of model resolution on water yield by using the SWAT model on the Missouri River Basin for a 25-year historical period and for GCM and RCM doubled CO<sub>2</sub> scenarios used to modify the historical data. They found that, compared to the historical climate, water yields were significantly greater for the doubled CO<sub>2</sub> scenarios for both GCM and RCM. They also found that yields produced by SWAT from RCM results were significantly greater than those simulated from GCM results and that there were substantial differences in RCM- and GCM-induced water yields across subbasins. They concluded that choice of climate model resolution affects estimation of water yield under climate change.

[8] *Arnell et al.* [2003] analyzed different ways of constructing climate change scenarios from a single climate model and found that these different scenarios could lead to differences in runoff of 10–20%. They use a regional climate model as their primary downscaling method and compare results with different downscaling techniques, including simple interpolation of global-model results and a time slice experiment. They also examine the relative merits of using climate model data directly to assess impacts of climate change versus applying a climate change signal to an observed baseline climate. The reports of both *Stone et al.* [2003] and *Arnell et al.* [2003] address uncertainties relating to spatial scales of the scenarios, but our study goes one step further to explicitly look at error in impacts resulting from the RCM itself. The availability of reanalysis data over a data-rich region such as the continental United States allows comparison of impacts resulting from an RCM driven by reanalyzed observations versus impacts derived from observed surface data, thereby allowing RCM error to be quantified.

[9] We have used 10-year simulations of contemporary (current) and future scenario climates for the United States to provide a physically consistent set of climate variables for input to a watershed-scale simulation model. The objective of this study was to explore streamflow, and

model-introduced uncertainty thereof, in a future scenario climate by introducing a regional climate model to dynamically downscale global model results to create data required by the streamflow model. The regional climate model is driven by a global model or global reanalysis of observed data to explore the accuracy of such a modeling system to simulate current conditions and to explore the precision (not accuracy) of the system for projecting streamflows consistent with a future scenario climate. By its use of three sets of 10-year simulations of climate for the region, this study provides a first step in exploring the potential impact on streamflow of fine-scale dynamics such as the low-level jet (as opposed to the role of orographically induced precipitation) that are known to influence precipitation in this region.

## 2. Models and Input Data

### 2.1. SWAT Model

[10] The SWAT model [*Arnold et al.*, 1998] is a long-term, continuous watershed simulation model. It operates on a daily time step and is designed to assess the impact of management on water, sediment, and agricultural chemical yields. The model is physically based, computationally efficient, and capable of simulating a high level of spatial details by allowing the watershed to be divided into a large number of subwatersheds. Major model components include weather, hydrology, soil temperature, plant growth, nutrients, pesticides, and land management. The model has been validated for several watersheds [*Rosenthal et al.*, 1995; *Arnold and Allen*, 1996; *Srinivasan et al.*, 1998; *Arnold et al.*, 1999; *Saleh et al.*, 2000; *Santhi et al.*, 2001].

[11] In SWAT, a watershed is divided into multiple subwatersheds, which are then further subdivided into unique soil/land use characteristics called hydrologic response units (HRUs). The water balance of each HRU in SWAT is represented by four storage volumes: snow, soil profile (0–2 m), shallow aquifer (typically 2–20 m), and deep aquifer (>20 m). Flow generation, sediment yield, and non-point-source loadings from each HRU in a subwatershed are summed, and the resulting loads are routed through channels, ponds, and/or reservoirs to the watershed outlet. Hydrologic processes are based on the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^t (R - Q_{surf} - ET - P - QR), \quad (1)$$

where  $SW_t$  is the final soil water content (mm),  $SW_0$  is the initial soil water content (mm), and  $R$ ,  $Q_{surf}$ ,  $ET$ ,  $P$ , and  $QR$  are the daily amounts (in mm) of precipitation, runoff, evapotranspiration, percolation, and groundwater flow on day  $i$  respectively. The soil profile is subdivided into multiple layers that support soil water processes including infiltration, evaporation, plant uptake, lateral flow, and percolation to lower layers. The soil percolation component of SWAT uses a storage routing technique to simulate flow through each soil layer in the root zone. Downward flow occurs when field capacity of a soil layer is exceeded and the layer below is not saturated. Percolation from the bottom of the soil profile recharges the shallow aquifer. If temperature in a particular layer is 0°C or below, no percolation is allowed from that layer. Lateral subsurface

flow in the soil profile is calculated simultaneously with percolation. Groundwater flow contribution to total streamflow is simulated by routing a shallow aquifer storage component to the stream [Arnold *et al.*, 1993].

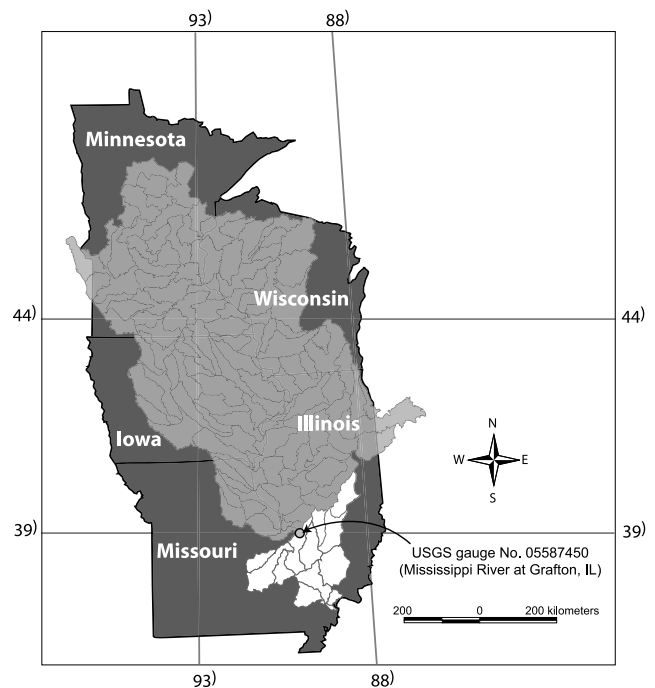
[12] Surface runoff from daily rainfall is estimated with the modified SCS curve number method, which estimates the amount of runoff based on local land use, soil type, and antecedent moisture condition. A provision for estimating runoff from frozen soil is also included. Snow melts on days when the daily maximum temperature exceeds 0°C. Melted snow is treated the same as rainfall for estimating runoff and percolation. Channel routing is simulated using the Muskingum method. The model computes evaporation from soils and plants separately. Potential evapotranspiration is modeled with the Hargreaves method. Potential soil water evaporation is estimated as a function of potential ET and leaf area index (area of plant leaves relative to the soil surface area). Actual soil evaporation is estimated by using exponential functions of soil depth and water content. Plant water evaporation is simulated as a linear function of potential ET, leaf area index and root depth and can be limited by soil water content. More detailed descriptions of the model are given by Arnold *et al.* [1998].

## 2.2. UMRB Watershed

[13] The UMRB has a drainage area of 431,000 km<sup>2</sup> up to the point just before confluence of the Missouri and Mississippi Rivers (Grafton, Illinois) and covers parts of seven states: Minnesota, Wisconsin, South Dakota, Iowa, Illinois, Missouri, and Indiana (Figure 1). Land cover in the basin is diverse, including agricultural lands, forest, wetlands, lakes, prairies, and urban area. The river system supports commercial navigation, recreation, and a wide variety of ecosystems. In addition, the region's more than 30 million residents rely on river water for public and industrial supplies, power plant cooling, wastewater assimilation, and other uses.

[14] The UMRB is in the region unique to the United States, where summertime mesoscale convective precipitation [Wallace and Hobbs, 1977] is dependent on nocturnal water vapor flux convergence [Anderson *et al.*, 2003]. Neither the NNR [Higgins *et al.*, 1997] nor global climate models [Ghan *et al.*, 1995] capture this essential mechanism. Finer grid spacing is needed to resolve the fine-scale dynamical processes that lead to timing, location, and amounts of precipitation [Anderson *et al.*, 2003]. Most, but not all, regional models (including the one used herein) are able to capture the nocturnal maximum in hourly precipitation in this region [Anderson *et al.*, 2003], which is an indicator that nocturnal moisture convergence at the outflow of the low-level jet is being simulated. For this reason, we expect that use of a regional climate model will improve on streamflow simulations driven by either reanalysis or global climate models.

[15] The SWAT model requires a variety of detailed information describing the watershed. Land use, soil and topography data of the UMRB were obtained from the Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) package version 3 [U.S. Environmental Protection Agency (USEPA), 2001]. Land use categories available from BASINS are relatively simplistic, providing (for instance) only one category for agricultural use (defined as "Agricultural Land-Generic"). Agricultural lands cover



**Figure 1.** The Upper Mississippi River Basin (UMRB) and delineated 8-digit HUCs.

almost 75% of the area. The soil data available in BASINS come from the State Soil Geographic (STATSGO) database [U.S. Department of Agriculture (USDA), 1994], which contains soil maps at a 1:25,000 scale. The STATSGO map unit is linked to the Soil Interpretations Record attribute database that provides the proportionate extent of component soils and soil layer physical properties (texture, bulk density, available water capacity, saturated conductivity, soil albedo, and organic carbon) for up to 10 layers. The STATSGO soil map units and associated layer data were used to characterize the simulated soils for the SWAT analyses. Topographic information is provided in BASINS in the form of digital elevation model (DEM) data. The DEM data were used to generate stream networks using the ArcView interface of SWAT (called AVSWAT). On the basis of the generated stream networks, 119 subwatersheds were then delineated up to the point just before the confluence with the Missouri River (see Figure 1). The delineated subwatersheds follow the boundaries of the USGS defined 8-digit hydrologic unit codes (HUCs). The HRUs were then created considering dominant soil/land use category within each subwatershed; that is, each subwatershed was assumed to be constituted with a single soil type and land use. The management operations for each HRU were the default values produced by AVSWAT. These management operations consist of planting, harvesting, and automatic fertilizer applications for the agricultural lands. No attempt was made to improve the management data because the main intent of the present study was to assess the impacts of climate change on hydrology, rather than on water quality of the region.

## 2.3. Climate Data

[16] SWAT requires daily precipitation, maximum/minimum air temperature, solar radiation, wind speed and relative humidity as meteorological input. In the absence

of supplied observations, the weather generator within SWAT uses its statistical database to generate representative daily values for the missing variables for each subwatershed. Ideally, at least 20 years of records are desired for the weather generator database. Data not supplied from the observations input file were generated internally by the model's weather generator. In this study we supplied daily precipitation and daily maximum and minimum temperature to SWAT either from observations or from the RCM. SWAT defines precipitation to be snow based on the relation of mean surface air temperature (determined from the daily minimum and maximum as  $(T_{\max} + T_{\min})/2$ ) to a threshold value established in calibration process.

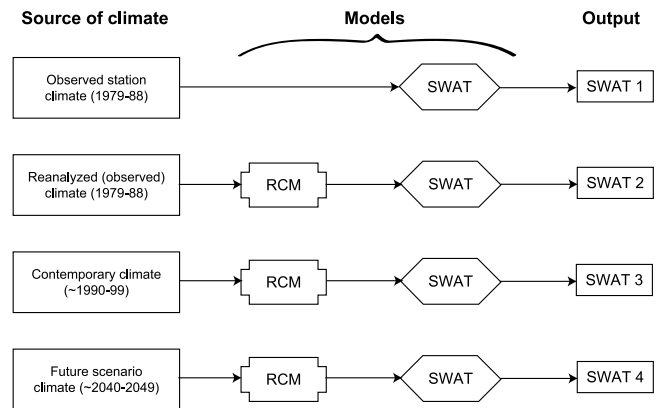
[17] SWAT accepts one set of weather information for each subwatershed. The SWAT modeling framework has 119 subwatersheds upstream of Grafton, Illinois, so the model requires 119 sets of weather information to produce the observations-driven simulations (e.g., output later referred to as SWAT 1). If more than one observing station falls within a subwatershed, SWAT chooses the one nearest the subwatershed centroid. A few subwatersheds have no observing station within their boundaries, so adjacent stations are used to provide temperature and precipitation data used by SWAT. For these reasons 99 of a possible 160 weather stations within the UMRB were used in this analysis.

[18] We used four sets of climate data to drive SWAT as shown in the left-hand column of boxes in Figure 2: one observed data set from stations and three sets of RCM simulated climate data. Observed data were extracted from the U.S. COOP database (National Climatic Data Center (NCDC), Cooperative Observer Program (COOP), <http://www.nws.noaa.gov/om/coop/Publications/>, 2000), as compiled by the Variable Infiltration Capacity group (VIC, <http://www.ce.washington.edu/pub/HYDRO/edm/>).

[19] The remaining three sets of climate data were generated using the regional climate model RegCM2 [Giorgi *et al.*, 1993]. The model simulation has a horizontal grid spacing of 52 km [Pan *et al.*, 2001], thereby providing approximately 160 grid points within the UMRB. The simulation domain centered at (100°W, 37.5°N) covers the continental United States and includes a buffer zone near the lateral boundaries (far from the UMRB) where the global information was introduced. Lateral boundary data were supplied for every model time step by interpolating 6-hourly data from the reanalysis and GCM. More details on the domain and implementation of boundary conditions for the regional model are described by Pan *et al.* [2001] and Takle *et al.* [1999].

[20] The NCEP/NCAR reanalysis (NNR) dataset [Kalnay *et al.*, 1996]  $1.875^\circ \times 1.875^\circ$  grid over the entire globe was downscaled onto RCM  $52 \times 52$  km grids. NNR combined all available observations for a 40-year period, including the 10-year period of the current study, with a dynamical model to maximize internal physical consistency and is considered to be most accurate in regions such as the UMRB where a relatively dense network of observing stations has provided the raw data. This downscaling simulation was used to examine the RCM's capability in producing observed climate for the specific period (1979–1988).

[21] The other two downscaling simulations are based on the GCM climates (rather than the NNR). The results of the GCM of the Hadley Centre (HadCM2) [Jones *et al.*, 1997]



**Figure 2.** Schematic diagram of RCM/SWAT simulation runs.

were used to provide the basic climate information for assessing the impact of climate change and uncertainty in this assessment. The HadCM2 [Jones *et al.*, 1997] is a coupled atmosphere-ocean model that uses a finite difference grid of  $2.5^\circ$  latitude by  $3.75^\circ$  longitude (about 300 km in midlatitudes). Only three grid points fall within the boundaries of the UMRB, which does not provide sufficient spatial climate detail to capture within-basin heterogeneity of atmospheric dynamical or hydrological processes. We nested a fine grid resolution RCM (RegCM2) into the coarse grid global model to dynamically downscale global information over the continental United States. The GCM contemporary climate represented by a 10-year window corresponds roughly to 1990s, selected from the HadCM2 simulations without enhanced greenhouse gas (GHG) forcing [Jones *et al.*, 1997]. The future scenario climate is from a transient simulation that assumed a 1% per year increase in effective GHGs after 1990. Sulfate aerosol effects (of secondary importance for this region) were not included in the transient GHG simulations used in this paper. The 10-year window selected for the scenario climate corresponds to 2040–2049 with  $\text{CO}_2$  about 480 ppm. A more detailed description is given by Pan *et al.* [2001].

[22] Any climate-impacts study based on RCM results will depend strongly on the particular GCM and particular emissions scenario used to force the RCM for future climate. We used the HadCM2 model, which has a transient climate response of  $1.7$  ( $1.7^\circ\text{C}$  global temperature rise at time of  $\text{CO}_2$  doubling) compared to a mean (standard deviation) value of  $1.8$  ( $0.43$ ) for the 19 models listed by the IPCC [IPCC, 2001a]. The equilibrium sensitivity of HadCM2 is  $4.1$  whereas the 17 models tabulated by the IPCC have mean (standard deviation) of  $3.4$  ( $0.95$ ). For global precipitation change, HadCM2 produced slightly above the mean of models plotted.

[23] Although our regional modeling procedure downscales global fields from outside the continental United States and is therefore not dependent on HadCM2 results within the UMRB, it is informative to compare HadCM2 results over UMRB with those of other global models. On a regional basis, HadCM2 had lowest warming of 5 models ( $3.8^\circ\text{C}$  versus mean of  $5.2^\circ\text{C}$ ) summarized by the IPCC report for central North America for climate change be-

tween 2071–2100 and 1961–1990. Global models are highly inconsistent for precipitation amounts in the central North America with means (standard deviations) of +9% (6%) in winter and –9% (18%) in summer. HadCM2 gave about +16% for both seasons.

[24] In summary, HadCM2 is quite near the center of the range of climate sensitivities of global climate models, and for the specific region of our study HadCM2 results are somewhat wetter and slightly cooler than average for global models reported by the IPCC [2001a].

### 3. Model Uncertainties and Experimental Design

#### 3.1. Sources of Error

[25] This study is designed to evaluate both the projected change in streamflow due to climate change and the uncertainty or level of confidence in the results. Errors in estimating impact of climate change on streamflow come from (1) uncertainty in the assumption of future GHG scenarios, (2) errors in the GCM that translates the GHG emission into future scenario global climate, (3) errors in the downscaling of global results to regional climate (in our case, done by an RCM), (4) errors in SWAT, and (5) errors arising from choices made in combining models (e.g., use of evapotranspiration from the RCM or SWAT).

[26] For this study we have access to only one global model run for one GHG scenario, so we are unable to assess error 1. The GCM has errors in describing the current climate, and hence presumably in the future climate for the same (whatever) reasons. However, the GCM future scenario climate also may have errors emerging from the changes in GHG concentrations or their feedbacks that are not present in simulations of the contemporary climate. We term the GCM error for the contemporary climate as “error 2a” and the additional error due to changes in GHGs as “error 2b.” When models are linked together, the error arising from the linkage is likely not represented by a linear combination of individual model errors. By using various combinations of input conditions to the RCM and SWAT, we can calculate and intercompare different end-product streamflows, thereby gaining at least qualitative assessment of these combinational errors. This builds on the method used by Pan *et al.* [2001] but goes beyond the procedure used therein to include the impacts model in addition to the climate models.

#### 3.2. Experimental Design

[27] Figure 2 shows different SWAT runs with historical and RCM generated climates. Results of the first SWAT simulation (SWAT 1 in Figure 2) with the observed station climate from 1979–88 are compared with measured streamflows at Grafton, Illinois, during that same period to evaluate the capability of SWAT in representing observed discharges in the UMRB. It is not possible to make an unambiguous estimate of error introduced by the RCM, but a good proxy for this is a comparison of SWAT results produced when an RCM run driven by observed climate interpolated to the RCM grid (NNR, 1979–1988) with SWAT results produced by the observed climate (SWAT 1). This procedure minimizes impact of errors in SWAT but includes streamflow errors that may have originated in the reanalysis used to create input to the RCM. The contribution of NNR errors to this result is minimized by our choice of

**Table 1.** Definition of Errors in Simulated Streamflows and Climate Change

Comparisons	Evaluate
SWAT 1 versus measured	SWAT error
SWAT 2 versus SWAT 1	RCM error
SWAT 3 versus SWAT 2	GCM error
SWAT 3 versus SWAT 1	GCM-RCM error
SWAT 2 versus measured	RCM-SWAT error
SWAT 3 versus measured	GCM-RCM-SWAT error
SWAT 4 versus SWAT 3	climate change

lateral boundaries far from the UMRB and the fact that the RCM incorporates surface boundary influences at a higher spatial resolution than the NNR. Error 2a from the global model is evaluated by comparing output of SWAT driven by the RCM driven by the GCM for the contemporary climate (SWAT 3) with output of SWAT driven by the RCM driven by the reanalysis (SWAT 2). Daily maximum and minimum temperatures from the HadCM2 were not available to be used (along with daily precipitation) as input to SWAT, thereby precluding a more direct evaluation of the added value of the RCM.

[28] Errors arising within individual models may be amplified or compensated for when models are used in combination. Measured streamflow and various SWAT outputs can be combined in other ways to give additional insight on errors arising from the combined models. Table 1 lists various combinations that are available. The three individual model errors and three model-combination errors provide a backdrop for interpreting the change in streamflow due to climate change as determined by comparing results of SWAT driven by the RCM forced by the GCM results for the future scenario climate (SWAT 4) with SWAT 3.

#### 3.3. Error Assessment

[29] Ability of the hydrologic model and the climate model to simulate water yield was evaluated by computing bias and root mean square error (RMSE):

$$Bias = \frac{1}{N} \sum_{i=1}^N (Q_{S_i} - Q_{m_i}), \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Q_{S_i} - Q_{m_i})^2}, \quad (3)$$

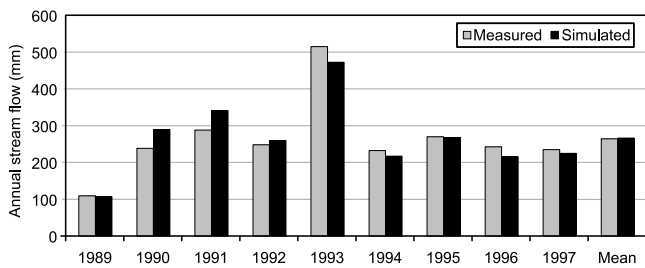
where  $Q_m$  and  $Q_s$  are the measured and simulated streamflow respectively, and  $N$  is number of years of streamflow data. The bias provides a measure of systematic errors revealed from comparing model results with measurements. The RMSE gives an estimate of the variability of the model compared with observations, which is used to assess the validity of the model in reproducing the seasonal cycle ( $N = 12$ ).

### 4. Results and Discussion

#### 4.1. Model Validation

##### 4.1.1. SWAT Calibration and Validation

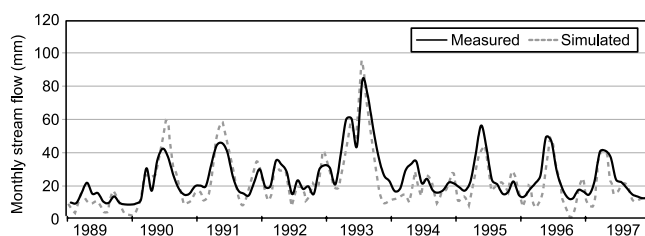
[30] Measured streamflows during 1989–1997 at USGS gauge station 05587450, Mississippi River near Grafton,



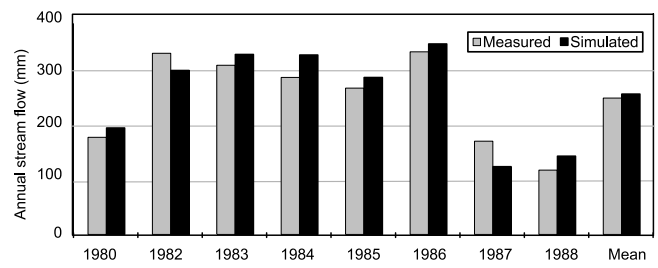
**Figure 3.** Measured and simulated annual streamflows at USGS gauge 05587450, Mississippi River near Grafton, Illinois, for calibration.

Illinois, were used to calibrate SWAT. The criterion used for calibrating the model was to minimize the difference between measured and simulated streamflow at the watershed outlet. No attempt was made to calibrate base flow and surface runoff independent of total streamflow, since only total flow data were available. The flow-related model parameters such as runoff curve number (CN), soil evaporation compensation factor (ESCO), plant uptake compensation factor (EPCO), re-evaporation coefficient (REVP), groundwater delay, and rain/snow temperature threshold were adjusted from the model initial estimates defaulted by AVSWAT to fit simulated flows to the observed ones. Detailed explanation of calibrated parameters can be found in the SWAT theoretical documentation, which is available online at <http://www.brc.tamus.edu/swat>. Comparison of annual flow (Figure 3) and time series (Figure 4) of monthly streamflow at the watershed outlet shows that the magnitude and trend in the simulated streamflows agreed with measured data quite well. Model performance was evaluated by the coefficient of determination ( $R^2$ ) and Nash-Sutcliffe simulation efficiency (E) [Nash and Sutcliffe, 1970]. If  $R^2$  and E values are less than or very close to zero, the model simulation is considered unacceptable. If the values approach one, the model simulations would be perfect. Statistical evaluation for annual simulation yielded an  $R^2$  value of 0.91 and E value of 0.91, indicating a reasonable agreement between the measured and simulated flows. For monthly simulations we calculated an  $R^2$  value of 0.75 and E value of 0.67.

[31] Flow validation was conducted using the streamflow data for the period from 1980 to 1988. Simulated streamflow for this period provides the output labeled SWAT 1 in Figure 2. During the validation process, the model was run with input parameters calibrated earlier without any change. Measured and simulated annual (Figure 5) and monthly



**Figure 4.** Time series of measured and simulated monthly streamflows at USGS gauge 05587450, Mississippi River near Grafton, Illinois, for calibration.



**Figure 5.** Same as Figure 3, but for validation.

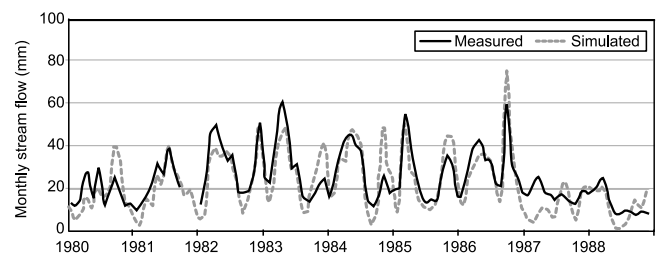
(Figure 6) streamflow show a good agreement between simulated streamflows and the measured values. Annual simulations yielded an  $R^2$  value of 0.89 and E value of 0.86, while an  $R^2$  value of 0.70 and E value of 0.59 were obtained for monthly simulations. Overall, the model was able to simulate streamflow with a reasonable accuracy. Other SWAT application papers considered the  $R^2$  values of more than 0.7 and E values of more than 0.5 as sufficient conditions for model validation on a watershed scale [Srinivasan *et al.*, 1998; Santhi *et al.*, 2001].

#### 4.1.2. Hydrological Components of SWAT and RegCM2

[32] RegCM2 has its own surface hydrology package but lacks a streamflow routing process, as contained in SWAT, that is an essential ingredient of this study. It is, however, informative to compare the hydrological components of RegCM2 and SWAT to shed light on whether uncertainty introduced by the RCM-SWAT combination might be attributable to discrepancies between these components. The key hydrological components are evapotranspiration, runoff, and snowmelt. Recall that precipitation is identical for both the models. The 10-year annual means of these components differ by only 6–10% between the two models (Table 2), which is perhaps surprising, given large differences in formulations of models' hydrology.

[33] Both RegCM2 and SWAT captured the seasonal trend of runoff that peaks in April. The SWAT-simulated peak is slightly earlier than that of RegCM2 (Figure 7b). The annual mean runoff values simulated by SWAT and RegCM2 are 12.6 mm and 13.8, respectively, within 10% agreement.

[34] Runoff is largely controlled by precipitation minus evapotranspiration ( $P - ET$ ). Although  $P$  is common to both models,  $ET$  can be different. RegCM2 simulated about 15% more  $ET$  than SWAT in June and July (Figure 7c), possibly associated with positive feedback between precipitation and evapotranspiration in RegCM2 that is not simulated in SWAT.



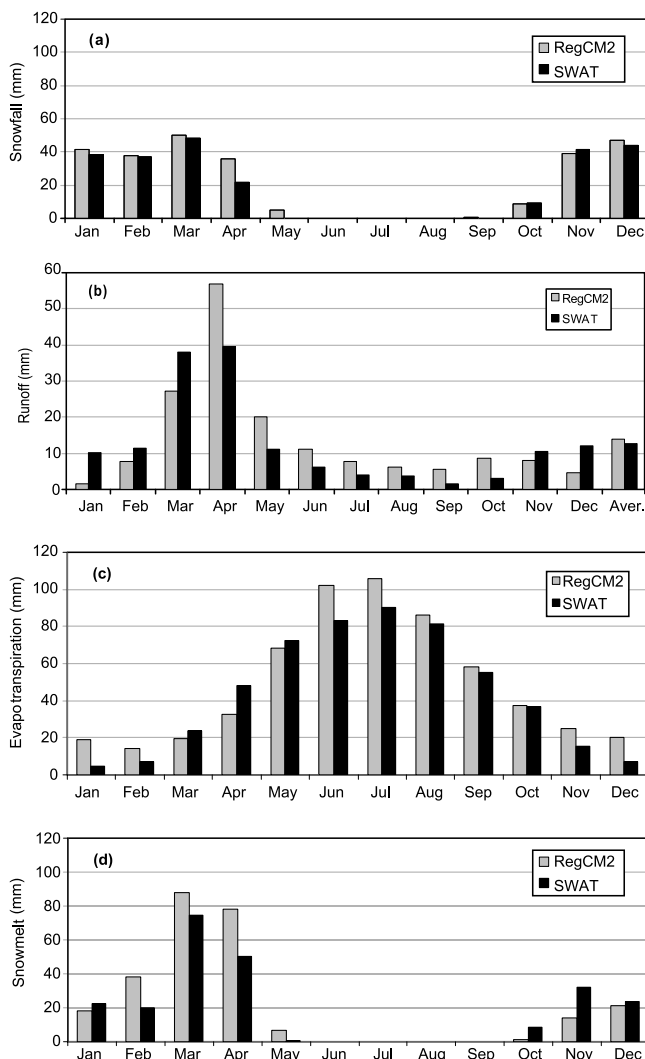
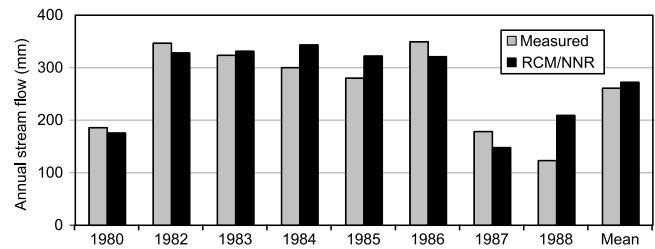
**Figure 6.** Same as Figure 4, but for validation.

**Table 2.** Hydrological Component Comparison Between RegCM2 and SWAT<sup>a</sup>

	RegCM2	SWAT
Evapotranspiration	588	528
Surface runoff	151	166
Snowmelt	256	240

<sup>a</sup>All values are in millimeters per year averaged for 1980–1988 in NNR run.

[35] RegCM2 produces a smooth curve of snowmelt that monotonically increases from a small value in October to a maximum in March and then drops to near zero in May (Figure 7d). In contrast, SWAT produces a November secondary maximum followed by a slight decrease through February before increasing to a March primary maximum and then decreasing to essentially zero in May. In RegCM2 the snow/rain threshold is established to be when the surface air temperature is 2.2°C. The value is 2.2

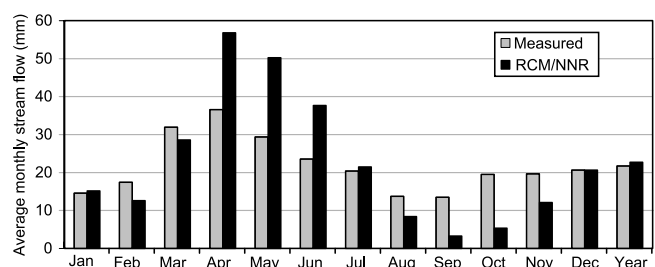
**Figure 7.** Comparison of hydrological components between RegCM2 and SWAT: (a) snowfall, (b) runoff, (c) evapotranspiration, and (d) snowmelt. All values are averaged for 1980–1988 for the NNR runs.**Figure 8.** Annual streamflows produced by SWAT driven by the RCM with NNR lateral boundary conditions, compared with measured streamflows at USGS gauge 05587450, Mississippi River near Grafton, Illinois.

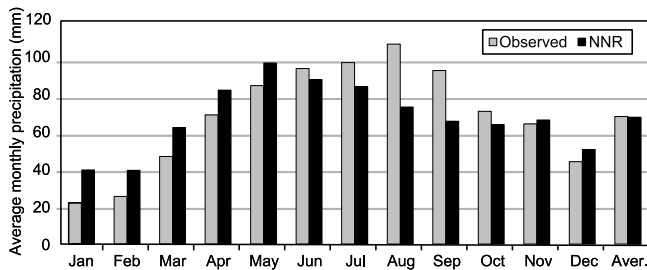
instead of zero because the precipitation temperature is typically lower than that of surface air. In RegCM2, the surface temperature is updated every time step, so a rain/snow decision is made every time step. SWAT, by contrast, defines the daily total precipitation to be snow if the mean surface air temperature (determined from the daily minimum and maximum as  $[(T_{\max} + T_{\min})/2]$ ) is equal to or below the rain/snow threshold temperature, determined in the calibration process to be 2.0°C. Despite of the difference in threshold values and the RCM time step versus SWAT daily partitioning, the resultant snowfall is very similar for the two models in all months except April and May when RegCM2 produces, respectively, 15 and 5 mm more snow water equivalent than SWAT (Figure 7a). Annual totals agree to within 5%.

#### 4.1.3. Combining SWAT With the RCM

[36] The calibrated SWAT model was run with weather inputs (precipitation and temperature) generated from the RCM model for the period 1979–1988 (labeled as NNR). The output is labeled as “SWAT 2” in Figure 2. The annual simulation matched well with the measured data, as shown in Figure 8. It is noteworthy that the year having the largest error was 1988, a year of extreme drought in the central United States. Statistical evaluation revealed that the model was able to explain at least 77% of the variability in the measured streamflow ( $R^2 = 0.77$ ), showing a reasonably good agreement between measured and simulated streamflows.

[37] Streamflow is an integrator of climate processes, both spatially and temporally. Since there is essentially no change in in-basin storage from year to year, what goes

**Figure 9.** Comparison of measured mean monthly streamflows and those produced by SWAT driven by the RCM downscaled NNR data for the validation period (1980–1988).



**Figure 10.** Same as Figure 8, but for precipitation.

in as precipitation must come out at streamflow. The RCM gives a very good estimate of mean annual precipitation (Figure 10) and interannual variability of annual streamflow (Figure 8) over the basin. However, on sub-annual timescales, errors in the regional model, in addition to errors in routing and timing of snowmelt, can introduce errors in streamflow that put additional limitations on this method for impacts assessment on such timescales. This shortcoming at shorter timescales and their compensating tendency for the annual total provides a measure of caution for interpreting the errors in annual estimates.

[38] *Mearns et al.* [1997] examine the impact of changes in both mean and variance of climate on output of a crop model and demonstrated the importance of including variability. A more in-depth study using the *Mearns et al.* [1997] procedure is needed to investigate the extent to which the integrating nature of streamflow would suppress the importance of short-term variability in climate.

[39] Errors in simulating monthly streamflow are shown in Figure 9. In spring, streamflow is very sensitive to surface and subsurface temperatures and to whether precipitation falls as rain or snow, this latter feature also being a sensitive function of temperature near the ground. In a comparison of RegCM2 climate variables with observations for three snowfall-dominated basins, *Hay et al.* [2002] found that model errors in temperature were more detrimental than errors in precipitation in assessing time-integrated runoff. RegCM2 has a warm bias for winter daily minimum temperatures, which likely is contributing to excessive early spring runoff and amplification of the seasonal cycle (Figure 9). Seasonal distribution of precipitation shown in Figure 10 suggests that

excesses in model-generated precipitation in winter also contributed to the excess spring streamflow. Similarly, lower estimated precipitation in summer months likely contributed, along with excessive early season runoff previously mentioned, to the low streamflow simulated for August through November. This is also evident in the analysis of hydrological budget components discussed in a later section of this paper.

[40] *Giorgi et al.* [1994b] analyzed the surface hydrology of a multi-year simulation of the climate over the United States with an RCM (RegCM) nested within a GCM and compared results with available observations. For the Mississippi River Basin, they found that the model under-predicted precipitation, evaporation and surface runoff, and over-predicted the temperature on an average annual basis. When the RCM-produced precipitation and temperature were used herein to drive SWAT for the UMRB simulation, a similar underprediction was observed for evaporation, but surface runoff was reproduced very well (by SWAT rather than the RCM) on an average annual basis (see Table 3). By introducing SWAT for the hydrologic components we were able to compare our results against measured streamflow rather than runoff as was done by *Giorgi et al.* [1994b]. The combined modeling system simulated the hydrology very well on an annual basis, probably because of more accurate representation of topography, land use, and soil characteristics.

#### 4.2. Climate Change Impact Assessment

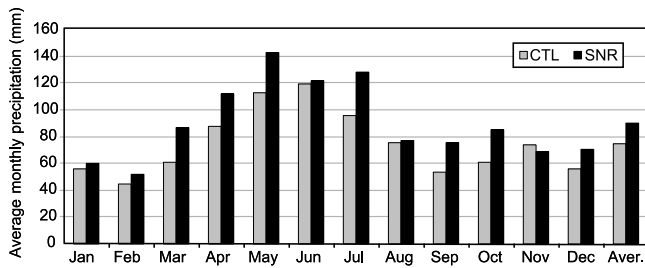
[41] The impact of climate change on hydrology was quantified by driving the calibrated SWAT model with RCM generated weather corresponding to the contemporary (labeled as CTL) and future scenario (labeled as SNR) climates nested in the global model as denoted by SWAT 3 and SWAT 4, respectively, in Figure 2. The analysis was performed on a monthly basis for streamflows and annual basis for hydrological budget components.

[42] Comparison of precipitation generated for contemporary and future scenario climates (Figure 11) suggests higher average values of monthly flows throughout the year in the future scenario, except for November, which has 2% lower than the current precipitation. Projected increases in precipitation for this region are consistent with trends over the last decades of the twentieth century [IPCC, 2001a]. The mean annual precipitation is projected to increase by 21%.

**Table 3.** Simulated Hydrologic Budget Components by SWAT Under Different Climates<sup>a</sup>

Hydrologic Budget Components	Calibration (1989–1997)	Validation (1980–1988)	NNR (1980–1988)	CTL (Around 1990s)	SNR (Around 2040s)	Percent Change (SNR-CTL)
Precipitation	856	846	831	898	1082	21
Snowfall	169	103	237	249	294	18
Snowmelt	168	99	230	245	291	19
Surface runoff	151	128	151	178	268	51
GW recharge	154	160	134	179	255	43
Total water yield	273	257	253	321	481	50
Potential ET	947	977	799	787	778	–1
Actual ET	547	541	528	539	566	5

<sup>a</sup>All units are in millimeters; precipitation values for NNR, CTL, and SNR are the outputs of the RCM model, and precipitation values for calibration and validation periods are from weather stations; other components are estimated by SWAT; total water yield is the sum of surface runoff, lateral flow, and groundwater flow.



**Figure 11.** Precipitation generated by the RCM for contemporary and future scenario climates.

[43] Climate-induced streamflow changes are inferred by evaluating differences produced by SWAT when driven by future scenario and contemporary climates. Annual average streamflow increased by 50% because of climate change (Figure 12), with the largest increase occurring in spring and summer. This disproportionate change, i.e., 50% increase in average annual streamflow versus 21% increase in average annual precipitation, can be attributed to more precipitation falling on saturated soils, which creates disproportionately large runoff. For instance, for a rain event producing, say, 10 cm of precipitation, the last several cm likely contribute completely to runoff and immediately to streamflow rather than soil infiltration that delays contribution to streamflows.

[44] Simulated hydrologic budget components under different sources of climate data (Table 3) provide insight into major sources of uncertainty in this combined-model study. Precipitation, being the primary input to the hydrological system, ranges from 831 to 898 mm per year (a variation of 8%) for the various contemporary climates (e.g., all columns except SNR). This remarkable consistency, however, masks RCM problems with monthly distributions as previously discussed. Other components except actual ET are far less consistent among the various contemporary climates, which suggests substantial interdecadal variability in the climate for these components, e.g., snowfall and snowmelt, in calibration versus validation decades, and/or model-generated differences, e.g., differences between validation and NNR columns. Largest variations were found in snowfall and related snowmelt and potential evapotranspiration estimation. These can be attributed, in part, to the error in seasonal precipitation simulation by the RCM (Figure 10).

[45] Despite large variations in budget components, annual simulations of total water yield are quite similar, especially between observed (validation period) and NNR conditions. Proportionate but higher values of budget components were found for CTL compared to NNR simulation runs, although they represent similar time domains, suggesting the GCM is biased toward high precipitation and a more intense hydrological cycle. This consistent bias among hydrological components can be expected in both GCM contemporary and future scenario climates.

[46] With the 21% increase in precipitation and accompanying changes in temperatures for the future scenario climate as simulated by the RCM, SWAT produced an 18% increase in snowfall, a 19% increase in snowmelt, a

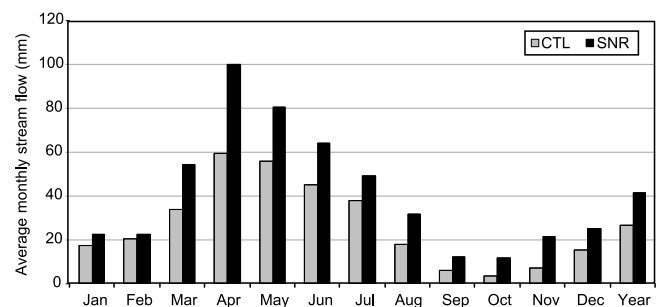
51% increase in surface runoff, and a 43% increase in recharge, leading to a 50% net increase in total water yield in the UMRB. Uncertainties in these projections are analyzed by the plan mapped out in Figure 2.

### 4.3. Uncertainties in Climate Change Impact Assessment

[47] Table 4 lists the absolute and relative bias and RMSE for all sources of errors in simulations of water yield of the Mississippi River at Grafton, Illinois. The highest percentage bias (18%) was found for GCM downscaling error. However, the highest individual model RMSE (14.3 mm) was found in RCM performance. RCM model simulation error was low on the annual basis (Figure 8), but high for seasonal values (Figure 9).

[48] The magnitude of the climate change can be considered a “signal” that we can compare to uncertainties arising from the various components of the modeling system, which can be considered “noise.” A high signal-to-noise ratio is a necessary (but not sufficient) condition for high confidence in using this modeling approach to accurately project future streamflows in the UMRB. As shown in Figure 13, change in streamflow (50%) due to climate change exceeds both individual model biases and also the combined-model bias, thereby providing a high signal-to-noise ratio. This result does not by itself ensure accuracy of the projection of future streamflow (i.e., does not provide the sufficient condition); however, if future global climate models are judged to be able to produce accurate future scenario climates with high confidence, then the combined-modeling procedure we have described provides a means of assessing confidence in the resulting streamflow.

[49] Annual streamflow tends to have a quasi-linear relationship with annual precipitation. We used regression analysis to evaluate this relationship (Figure 14) for the five options depicted in Figure 2. Table 5 lists the 5 regressions with their slope values. The regression line plotted represents measured annual streamflow versus observed annual precipitation for 1980 through 1997. We applied the pooled t-test to the regression-line slopes for the various sets of simulated results to determine whether any of these climates have relationships between streamflow and precipitation that differ significantly (at the 5% significance level) from observed. We found that the slopes for SWAT1 and SWAT3 are not different from the observed but that SWAT2 and SWAT4 are different from



**Figure 12.** Mean monthly streamflow simulated by SWAT for contemporary and future scenario climates.

**Table 4.** Bias and RMSE in Various Simulations of Water Yield of the Mississippi River at Grafton, Illinois<sup>a</sup>

Modeling Error	Absolute and Relative Bias in Average Monthly Simulation, mm	RMSE in Average Monthly Simulation, mm
SWAT	+0.6 (3%)	5.5
RCM	+0.3 (1%)	14.3
GCM	+4.0 (18%)	7.2
GCM-RCM	+4.3 (19%)	18.0
RCM-SWAT	+1.0 $\pm$ 4%	11.1
GCM-RCM-SWAT	+5.0 (23%)	14.5

<sup>a</sup>Refer to Table 1 for different modeling errors, to equation (2) for bias, and to equation (3) for RMSE.

the observed data and different from each other. This means that SWAT produces the same relationship between precipitation and streamflow as is observed and that SWAT driven by a regional model used to downscale global climate model results does also. However, more streamflow per unit of precipitation is produced when the NNR drives the regional model. And the future scenario climate as represented by the combined models has an even higher ratio.

[50] It is perhaps notable that the RCM/NNR results show the lowest annual streamflow bias (Figure 13) but the largest bias in the regression of annual streamflow with annual precipitation for the current climate (items 1–4 in Table 5). We suspect this might be further evidence of RCM inadequacies in simulating accurately the annual cycle of precipitation, although we have not done confirming experiments. Although the RCM produces an accurate annual total precipitation (Figure 10), it produces too much precipitation from November–May and less than observed from June–October. Warm-season precipitation contributes much more than cold-season precipitation to moisture recycling. However, recycled moisture does not contribute to streamflow (presuming it falls, evaporates, and re-falls within the basin): recycling allows higher annual precipitation for a given streamflow, and recycled moisture will contribute a larger absolute amount to annual precipitation in wet years. Therefore a model that is deficient in moisture recycling during the year will have a larger slope in the plot of annual streamflow versus annual precipitation.

[51] Then why is the RCM/CTL slope comparable to that of the observations rather than that of the RCM/NNR model, since the RCM presumably does not capture the seasonal cycle for the contemporary climate? We suspect the answer lies in the June–August rainfall totals, which approximate the observed values for the contemporary climate but are 18% low for the RCM/NNR climate

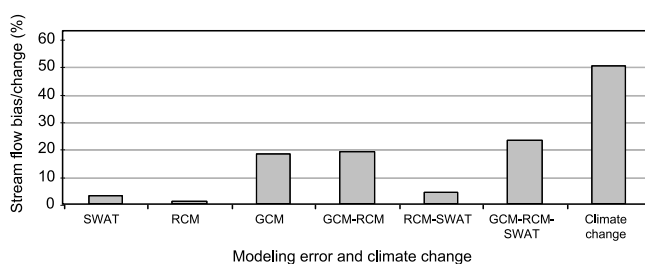
(Figures 10 and 11). These midsummer rains recharge the region's soils that are deep and have high moisture-holding capacity. Crops in the region develop deep roots by late summer and therefore efficiently contribute to moisture recycling by drawing moisture from the deep-soil reservoir that has been fully charged near the summer solstice.

[52] The seasonal trend in precipitation in the GCM future scenario climate (SNR) follows that in the CTL climate but with higher magnitude in all months. The regression slope calculated for the SNR climate was 1.16, a factor of 2 more than those of the contemporary climates. It should be noted that the slope greater than 1 does not mean more runoff than precipitation, but simply reflects larger portion of rainfall transported as runoff because of high-intensity rainfall events in future climate [IPCC, 2001a].

## 5. Limitation of Coupled Modeling System

[53] Hydrological budget components provide an internally consistent view of the water cycling within a watershed. Each component should be calibrated and validated against the measurements before being used to simulate future climates. However, limited data availability does not afford such luxury. Total water yield from the watershed typically is available only in terms of streamflow. In this study, only streamflow is calibrated and validated at the watershed outlet since measurements of snowmelt, groundwater flow and evapotranspiration are not available. The resulting budget components, after the model is calibrated for total water yield, are believed to be in the appropriate range assuming that the model can simulate the process realistically. Other reported studies show that SWAT is capable of providing watershed-scale analysis and has been validated on many small and large watersheds for total water yield, evapotranspiration, and groundwater recharge depending upon the data availability. *Arnold and Allen* [1996] validated SWAT for all components of the water balance including groundwater recharge for three river basins in Illinois.

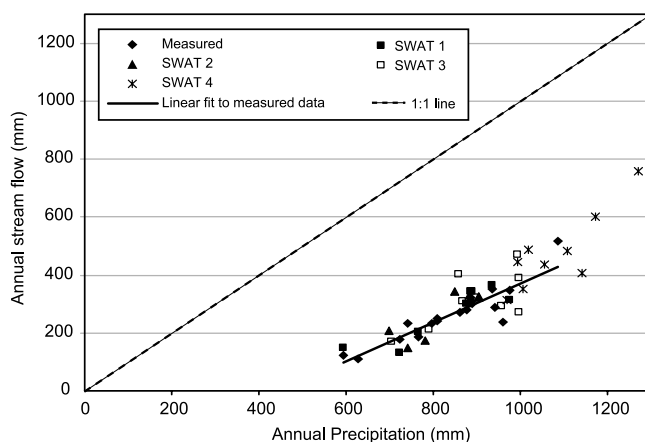
[54] In simulating the hydrologic cycle with RCM generated weather data, care should be taken to ensure that all budget components are changing in a proportional way. Known weaknesses in RCM simulation of snow water equivalent and high sensitivity of snow melt to air temperatures led to large errors in monthly streamflow beginning in spring. For these reasons we have low confidence in the ability of this coupled-model system to represent month-to-month streamflow.

**Figure 13.** Comparisons of climate change with annual biases in simulated streamflow.

[55] An additional limitation of this modeling procedure is the climate database used by the weather generator within SWAT. The statistical relationships used to find meteorological conditions not supplied by the RCM may be different in a future scenario climate from those used for the current climate. No allowance has been made for this potential difference in the present study. In principle, this limitation could be circumvented by allowing SWAT to ingest all the surface hydrological cycle information from the RCM. However, SWAT has far more detail on influences of land characteristics that would be lost in such a strategy. Alternatively, the future scenario climate of the RCM could be used to provide a more concurrent future scenario statistical database for the SWAT weather generator [Mearns *et al.*, 1997]. This might be a more suitable alternative, short of disassembling SWAT and reassembling it within the RCM.

## 6. Summary and Conclusions

[56] A regional climate model that generated two 10-year simulated climates for the continental United States corresponding to current and future scenario climates at 50 km horizontal resolution was used to drive a hydrological model, Soil and Water Assessment Tool (SWAT), over the entire UMRB. The objective of the study was to explore streamflow, and model-introduced uncertainty thereof, in a future scenario climate by introducing a regional climate model to dynamically downscale global model results to create temperature and precipitation data required by the streamflow model. Hydrologic components of the SWAT model were calibrated and validated using measured streamflow data at USGS gauge 05587450, Mississippi River near Grafton, Illinois. The model produced streamflow with reasonable accuracy on annual and monthly bases. Combined performance of SWAT and the RCM was first evaluated by driving SWAT with NNR data used as the RCM's lateral boundary conditions. This combined model system reproduced annual streamflow values well but failed to capture seasonal variability. Impact of climate change was then assessed by using two 10-year scenario periods (1990s and 2040s) generated by nesting the RCM into a coarse grid resolution global model (HadCM2). The combined GCM-



**Figure 14.** Relationship between annual streamflow and annual precipitation for various climates.

**Table 5.** Regression Analysis: Streamflow Versus Precipitation

	Streamflow Versus Precipitation	Scenario	Slope
1	Measured streamflow versus observed precipitation (1980–1997)	observed	0.66
2	Simulated streamflow versus observed precipitation (1980–1988)	SWAT 1	0.65
3	Simulated streamflow versus RCM/NNR precipitation (1980–1988)	SWAT 2	0.87
4	Simulated streamflow versus CTL precipitation (around 1990s)	SWAT 3	0.64
5	Simulated streamflow versus SNR precipitation (around 2040s)	SWAT 4	1.16

RCM-SWAT model system produced an increase in future scenario climate precipitation of 21% with a resulting 18% increase in snowfall, 51% increase in surface runoff, 43% increase in recharge and 50% increase in total water yield in the UMRB. This disproportionate change can be attributed to more intense precipitation events in future climates and the non-linear nature of hydrologic budget components, such as snowmelt, evapotranspiration, surface runoff, and ground-water flow.

[57] For the global climate model future scenario we used we have shown that the climate change signal is large relative to errors arising from the modeling procedure, with the largest error being attributable to the GCM downscaling error (18%), compared to a simulated change of 50% in annual streamflow. This gives confidence that such a downscaling procedure has value for impacts assessment provided the quality of the global model driving the RCM is high.

[58] Our results also suggest that the relationship of annual streamflow to annual precipitation may change in a future climate in that a unit increase in precipitation will cause a larger increase in streamflow. This may be due to increased recycling of moisture more uniformly from year to year in a future wetter climate. It also may be attributable to more intense precipitation events associated with mesoscale convective complexes that produce a larger fraction of runoff because of a more full soil profile in mid summer. It is known [Anderson *et al.*, 2003] that RCMs capture such mesoscale events more accurately than global models, strengthening the case for fine-scale resolution of the dynamics of the hydrological system, even in regions of little orographic forcing of precipitation, as being essential for driving hydrological impacts models.

[59] **Acknowledgments.** This research was sponsored by the Iowa State University Agronomy Department Endowment Funds, University of Iowa Center for Global and Regional Environmental Research, and the Biological and Environmental Research Program (BER), U.S. Department of Energy, through the Great Plains Regional Center of National Institute of Global Environmental Change under Cooperative Agreement 26-6223-7230-007. Computer resources used for this study were partly provided by the NCAR CSL facility. We acknowledge the perceptive comments of two anonymous reviewers, which led to substantial improvement of the paper.

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